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Pacific dominance to global air-sea CO_2 flux variability: A novel atmospheric inversion agrees with ocean models

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[1] We address an ongoing debate regarding the geographic distribution of interannual variability in ocean - atmosphere carbon exchange. We find that, for 1983–1998, both novel high-resolution atmospheric inversion calculations and global ocean biogeochemical models place the primary source of global CO_2 air-sea flux variability in the Pacific Ocean. In the model considered here, this variability is clearly associated with the El Niño/Southern Oscillation cycle. Both methods also indicate that the Southern Ocean is the second-largest source of air-sea CO_2 flux variability, and that variability is small throughout the Atlantic, including the North Atlantic, in contrast to previous studies. *INDEX TERMS:* 4806 Oceanography: Biological and Chemical: Carbon cycling; 0312 Atmospheric Composition and Structure: Air/sea constituent fluxes (3339, 4504); 4215 Oceanography: General: Climate and interannual variability (3309); 1615 Global Change: Biogeochemical processes (4805). **Citation:** McKinley, G. A., C. Rödenbeck, M. Gloor, S. Houweling, and M. Heimann (2004), Pacific dominance to global air-sea CO_2 flux variability: A novel atmospheric inversion agrees with ocean models, *Geophys. Res. Lett.*, *31*, L22308, doi:10.1029/2004GL021069.

1. Introduction

[2] Inversions of atmospheric data and ocean biogeochemical models have been shown to be in approximate agreement as to the amplitude of interannual variability in air-sea CO_2 exchange (extremes of ±0.5 PgC/yr) [*LeQuéré et al.*, 2003], but have differed regarding the geographic distribution of this variability [*McKinley et al.*, 2004; *LeQuéré et al.*, 2003; P. Peylin et al., Interannual CO_2 fluxes as deduced by inverse modeling of atmospheric CO_2 and by models of the ocean and the land carbon cycle, submitted to *Global Biogeochemical Cycles*, 2004, hereinafter referred to as Peylin et al., submitted manuscript, 2004]. Specifically, the importance of the middle and high latitudes to the global air-sea CO_2 flux variability is an issue of current debate [*McKinley et al.*, 2004; *Gruber et al.*, 2002; Peylin et al., submitted manuscript, 2004]. While ocean models find that the Equatorial Pacific dominates the global ocean flux variability, the inversion of *Bousquet et al.* [2000], as discussed by Peylin et al. (submitted manuscript, 2004), suggests that the Northern middle and high latitudes are significant to the global oceanic flux variability. *LeQuéré et al.* [2003] also indicate that the 3 inversions they consider disagree as to the geographic locations of the greatest air-sea CO_2 flux variability. The role of the North Atlantic in the global air-sea CO_2 flux variability has recently received particular attention. *Gruber et al.* [2002] extrapolate air-sea flux variability calculated from observed data at Bermuda for 1984 to 2000 and find that the pattern and magnitude of this estimate compares well to the North Atlantic CO_2 flux variability estimate from the inversion of *Bousquet et al.* [2000]. A relatively large flux variability from the region, with interannual extremes of ±0.3 PgC/yr, is suggested. However, ocean modeling studies predict that the North Atlantic CO_2 flux has a much smaller variability (*McKinley et al.* [2004] find extremes of ±0.07 PgC/yr), and that the Equatorial Pacific dominates the global ocean flux variability [*McKinley et al.*, 2004; *Obata and Kitamura*, 2003; *LeQuéré et al.*, 2000]. Though they strongly disagree in the North Atlantic, the *Bousquet et al.* [2000] inversion and models suggest very similar magnitudes and patterns of variability in the Equatorial Pacific [*McKinley et al.*, 2004; Peylin et al., submitted manuscript, 2004]. What drives these very different regional comparisons?

[3] *McKinley et al.* [2004] suggest that this may be a reflection of the specific inversion method used, in conjunction with the differences in the large-scale coherence in air-sea flux anomalies at high latitudes compared to the tropics. While traditional large-region inversions are well-suited for estimating flux anomalies characterized by basin-scale correlation lengths, they induce enhanced uncertainty for regions with shorter correlations. The problem is aggravated for two reasons. First, studies based on various methods [*LeQuéré et al.*, 2003; *Rödenbeck et al.*, 2003; Peylin et al., submitted manuscript, 2004; P. Tans, personal communication, 2004] indicate that ocean flux variability is smaller than land variability. Because atmospheric stations sample both land and ocean flux signals and inversions conserve mass, small relative errors in land flux estimates cause large relative errors in flux estimates in adjacent ocean regions. Second, the inverse problem of atmospheric transport is ill-posed: results are very sensitive to inconsistencies between inverse model and data [*Heimann et al.*, 2004]. Large-region inversions are more prone to these sources of error.

2. Models

[4] Methodology of the atmospheric inversion is described in detail by *Rödenbeck et al.* [2003]. Surface exchange CO_2 fluxes are estimated on the basis of atmospheric CO_2 concentration data, measured by NOAA/CMDL (National Oceanic and Atmospheric Administration/Climate Monitoring and Diagnostics Laboratory). Using an atmo-

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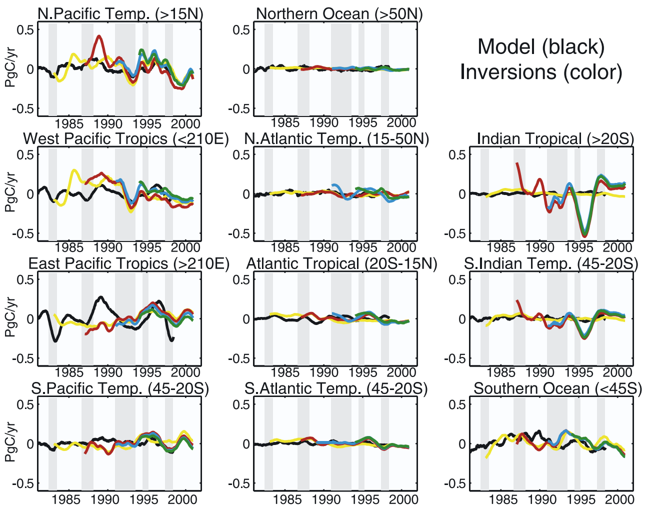

Figure 1. Regional comparison of model (black) to inversion (11-station (yellow), 16-station (red), 19-station (blue), and 26-station (green)) anomaly results. For clarity, model results are once-smoothed, and inversion results are twice-smoothed over 12 months. Gray regions are El Niño periods (when SST in the Niño 3.4 region is greater that 0.4°C). Positive fluxes are to the atmosphere.

spheric tracer transport model to link surface fluxes and atmospheric concentrations, the inversion technique determines those fluxes that give the best match between modeled and observed concentrations. The transport model (the TM3 offline atmospheric tracer transport model [*Heimann and Körner*, 2003] with resolution ≈4° × 5° and 19 vertical levels), is driven by reanalyzed meteorological data from the National Center for Environmental Prediction (NCEP) reanalysis which, in contrast to previous published inversions, vary interannually. In comparison to previous inversion calculations, fluxes are estimated on a much higher resolution grid (≈8° × 10°) to avoid aggregation errors arising otherwise from flux estimation on large regions with predefined internal structure. To stabilize the inverse calculations, a priori information on fluxes and their correlation structure is imposed in a Bayesian framework. Global annual mean a priori flux uncertainties of 1.0 PgC/yr for oceans and 2.7 PgC/yr for land regions are spatially distributed according to the flux estimates of *Takahashi et al.* [1999] for oceans and predictions of the LPJ land ecosystem model of S. Sitch et al. (unpublished manuscript) as cited by *Sitch* [2000] for land. The *a priori* information is the same each year such that any interannual variations in the flux estimates are driven only by the atmospheric data and the winds. As the spatial resolution of information is set by the data density, only fluxes recombined over correspondingly large areas are meaningful and will be used in the comparison here.

[5] As done by *Rödenbeck et al.* [2003], we present multiple inversion results, derived from runs of different time periods with decreasing lengths corresponding to an increasing number of available observation sites. Sites are selected so that data records span the complete period of the respective calculation. This is done in order to avoid spurious interannual variability. The runs with 11, 16, 19 and 26 sites, when smoothed, are valid for the periods 1983–2000, 1987–2000, 1991–2000 and 1994–2000, respectively.

[6] The biogeochemical ocean model is an offline version of the MITgcm [*Marshall et al.*, 1997; *McKinley et al.*, 2004]. Resolution is 1° in longitude and varies from 0.3° latitudinal resolution in the tropics to 1° at high latitudes. There are 47 vertical levels. The biogeochemical model is forced with 10 day-average output from the physical model which was forced with 12 hourly winds and heat and freshwater fluxes from the NCEP reanalysis for the period 1980–1998. Tracers are total phosphorus (P), O_2, and dissolved inorganic carbon. A simplified parameterization for particle export is used where light and nutrient limitation are explicit and other controls on biological export are grouped into a parameter chosen to maintain the nutrient climatology on the basin-scale. Net freshwater fluxes to the surface layer are used to drive a dilution, or virtual flux, of tracers. Both gas exchange and export production are reduced proportional to sea ice cover. The offline biogeochemical model is run only in the upper ocean (0–1265 m), and tracers relax to climatological concentrations over the three deepest layers (965–1265 m). Model results presented here are detrended to compensate for model drift.

3. Results

[7] In Figure 1, we compare model and inversion results for flux anomalies over 11 ocean regions as defined in the TransCom3 project [*Gurney et al.*, 2002]. Magnitudes of the variations are similar between the two methods in all regions except in the Indian Ocean. This variability may be related to changes in the sampling location and procedures at the Seychelles station prior to July 1996 (T. Conway, personal communication, 2004). In the Pacific regions, there is a relatively large variability (extremes up to ±0.4 PgC/yr). In the Southern Ocean, variability has extremes of ±0.2 PgC/yr. In all Atlantic regions, variability is small (extremes <0.1 PgC/yr).

[8] Though the amplitudes of the variability in these regions compare reasonably well, the patterns of temporal variability generally do not. This is not surprising from the inversion, given the sparse spatial density of the data which tends to allocate flux variability near station locations. When regions are aggregated, evidence of agreement emerges.

[9] In Figure 2, we present time-series aggregated over the globe and over the four Pacific regions. In Table 1, we present correlation analysis of model results, the inversion

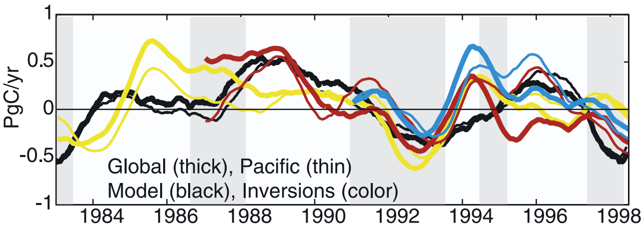

Figure 2. Comparison of Global (thick) and Pacific (thin) flux variability time-series of the 11-station (yellow), 16-station (red), 19-station (blue) inversions of *Rödenbeck et al.* [2003] and the ocean model (black). Model results are once-smoothed, and inversion results are twice-smoothed over 12 months. Gray regions are El Niño periods as defined in Figure 1.

Table 1. Timeseries Correlations[abc]

	1983–1998[d]	1987–1998[e]	1991–1998[f]
Inversion, Rödenbeck et al. [2003]			
Global to Model Global	0.23	0.34	0.19
	(0.95)	(0.98)	(<0.90)
Pacific to Model Pacific	0.12	0.50	0.40
	(<0.90)	(0.99)	(0.98)
Pacific to Global	**0.91**	**0.69**	**0.79**
	(0.99)	(0.99)	(0.99)
Pacific to SOI	−0.04	0.27	0.10
	(<0.90)	(0.95)	(<0.90)
max Pacific to SOI[g]	0.27[+5]	0.34[+2]	0.22[+4]
	(0.95)	(0.98)	(<0.90)
Alternate Inversion Without Seychelles			
Global to Model Global	-	0.36	0.16
	-	(0.98)	(<0.90)
Pacific to Model Pacific	-	0.40	0.16
	-	(0.99)	(<0.90)
Pacific to Global	-	**0.92**	**0.93**
	-	(0.99)	(0.99)
Pacific to SOI	-	0.20	−0.06
	-	(<0.90)	(<0.90)
max Pacific to SOI	-	0.30[+4]	0.14[+6]
	-	(0.95)	(<0.90)
Model			
Pacific to Global	**0.93**	**0.93**	**0.92**
	(0.99)	(0.99)	(0.99)
Pacific to SOI	**0.75**	**0.73**	**0.64**
	(0.99)	(0.99)	(0.99)
max Pacific to SOI	**0.80[+2]**	**0.78[+3]**	**0.76[+3]**
	(0.99)	(0.99)	(0.99)

[a]Inversion and model results are averaged to 4 month means such that the resulting time-series are in good approximation white noise processes, judged with help of the test of *Tong* [1990, p. 324]. We use 4 month averages because application of the test over increasing number of months levels off at 4 months.

[b]In parenthesis, we list the outcome of a significance test based on the statistic $t = \sqrt{n-2} * \frac{R_n}{\sqrt{1-R_n^2}}$ where R_n is the correlation coefficient, calculated using 4 monthly averaged time-series, and n is the sample size, noted below.

[c]Bold results are those that pass three criteria: (1) correlation $\geq$0.64, (2) correlation highly significant and (3) autocorrelations of both 4 monthly average time-series negligible.

[d]11-station, yellow in Figures 1 and 2, n = 51. Seychelles not used by *Rödenbeck et al.* [2003], so there is no alternate result.

[e]16-station, red in Figures 1 and 2, n = 39.

[f]19-station, blue in Figures 1 and 2, n = 27.

[g]Maximum Pacific correlation with the Southern Oscillation Index (SOI) found when the flux leads by the number of months noted in square brackets.

of *Rödenbeck et al.* [2003] and an alternate inversion where the Seychelles station is excluded for the 16 and 19-station inversions. Removal of Seychelles from the inversion eliminates the large variability in the Indian Ocean and surrounding regions seen in Figure 1, particularly in 1995–1996. We do not consider the 26-station inversion result further because it allows for only 4 years of overlap with the model result. In Table 2, we present the percent of the global variance described by the Pacific, Southern Ocean, and North Atlantic for the inversions and the model.

[10] Figure 2 and Tables 1 and 2 show us that in both the model and the inversion, the globally integrated air-sea CO_2 flux variability is clearly driven from the Pacific. While the Pacific explains 60% or more of the global variance, the Southern Ocean explains 4.5 to 9.2% and the North Atlantic about 0.72 to 7.1% (Table 2). Table 1 shows that if Seychelles is not included in the inversion, correlations between the global time-series and the Pacific time-series are 0.91 to 0.93. With Seychelles, correlations are still high (0.69 to 0.79). Correlations are 0.92 to 0.93 between the model's Pacific and global timeseries.

[11] Variability in the modeled Pacific flux is highly correlated with the Southern Oscillation Index (SOI) over all three time periods (Table 1). Though the inversions clearly indicate dominance of the Pacific to the global air-sea flux variability, the inversion time-series do not exhibit large correlation with the SOI, i.e., a clear ENSO signal is not found. The correlation with ENSO is mainly spoiled by the large positive anomaly in 1994 in the inversion results, for which we have not been able to determine a clear cause. In the inversion of *Bousquet et al.* [2000], equatorial Pacific CO_2 efflux rises and falls with La Niña and El Niño, respectively, however flux correlations with the SOI are not reported. For both this model and these inversions, correlations increase when the flux leads by 2–5 months, in agreement with *Rayner et al.* [1999].

4. Discussion

[12] Why is it that the Pacific Ocean dominates the global air-sea CO_2 flux variability? Observational work in the Equatorial Pacific [*Feely et al.*, 2002] and analysis of this and other models [*McKinley et al.*, 2004; *Obata and Kitamura*, 2003; *LeQuéré et al.*, 2000, 2003] has illustrated the enormous impact of ENSO on air-sea CO_2 fluxes. Across the equatorial Pacific, changes in the depth of the thermocline, upwelling rates, and the longitudinal displacement of the western Pacific warm pool drive surface ΔpCO_2 shifts; and changes in surface wind speeds alter air-sea exchange. With ENSO, the changes are coordinated over a large portion of the ocean, and substantial net air-sea CO_2 anomalies occur.

[13] These changes can be seen as a large-scale modulation of the physical processes responsible for the large net CO_2 efflux in the Equatorial Pacific. Why is it then that in the North Atlantic, where the net CO_2 uptake is large, physical modulation of the driving physical processes does not appear to result in a large air-sea flux interannual variability? Detailed analysis of this model shows that North Atlantic variability is small because convectively-

Table 2. Regional Percent of Global Variance[a]

	1983–1998	1987–1998	1991–1998
Inversion, Rödenbeck et al. [2003]			
Pacific	60%	77%	121%
Southern Ocean	6.3%	4.5%	6.4%
North Atlantic	0.80%	0.72%	7.1%
Alternate Inversion Without Seychelles			
Pacific	-	65%	61%
Southern Ocean	-	5.5%	9.2%
North Atlantic	-	0.80%	6.8%
Model			
Pacific	85%	85%	94%
Southern Ocean	5.2%	6.0%	4.5%
North Atlantic	1.1%	1.2%	1.6%

[a]Percent of variance = 100 $\cdot$ ($\sigma^2_{region}/\sigma^2_{global}$). Cancellation of regional anomalies can cause $\sigma^2_{region} > \sigma^2_{global}$ and thus the percent variance to be $\geq$100%.

produced dissolved inorganic carbon anomalies are damped by biological carbon export before substantial air-sea flux anomalies can occur. Heterogeneity of the variability in the driving processes also promotes cancellation when summed to the regional or basin scale [*McKinley et al.*, 2004]. Similar mechanisms may be at play in the Southern Ocean, though more study is clearly needed.

[14] Why is it that the *Rödenbeck et al.* [2003] inversion, unlike previous inverse calculations, agrees with the ocean model predictions? The spatially highly resolving inversion methodology used here limits the region of influence of a station to a smaller region than the large, basin-scale regions used in traditional approaches such as TransCom3. It therefore is able to limit errors caused by biases in the a priori prescribed large-scale flux patterns. In the *Rödenbeck et al.* [2003] approach, a priori correlations are applied to prevent gridscale noise, but this is a much softer and homogenous constraint than fixed regional structures. The downside to this approach, as already mentioned, is that it tends to allocate variability closer to the observation stations. Our results suggest that for areas with high spatial heterogeneity in the flux variability, such as the North Atlantic, this new inversion methodology is more appropriate than traditional approaches [*Bousquet et al.*, 2000; *Gurney et al.*, 2002]. As shown by sensitivity testing [*Rödenbeck et al.*, 2003], region size is indeed an important parameter affecting the flux estimates. For the same reason, the new approach is expected to be superior in allocating variability to different oceans like the Pacific and the Atlantic, and this is supported by the model-inversion comparison presented in this paper.

5. Conclusions

[15] We find that a novel, high-resolution atmospheric data inversion agrees with ocean biogeochemical models as to the dominance of the Pacific Ocean to the global air-sea CO_2 flux variability. Both methodologies also indicate that variability coming from the Southern Ocean is of secondary importance, and that variability throughout the Atlantic is small.

[16] These comparisons illustrate that important progress is being made in our capacity to observationally constrain and model the driving processes of air-sea carbon exchange variability. The inversions and model shown here do not, however, formally agree as to the temporal patterns of air-sea CO_2 flux variability at either the local or global scale. Future efforts need to focus on increasing data density, refining inversion methodology, and improving ocean biogeochemical models.

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